Sound Classification and Localization Based on Biology Hearing Models and Multiscale Vector Quantization

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Motivation

- **Algorithms motivated by similar processing in animals and humans:**
  - **Hearing and sound classification**
  - **Vision and identification of objects**
- **Text-independent robust speaker identification**
  - **Identifying the speaker from the "music" of his voice**
- **Speaker-independent speech recognition**
  - Identifying phonemes, vowels, words from their inherent sounds
- **Identification of musical instruments ("timbre")**

Applications to acoustic signal recognition

- **Fault identification in tools and wear prediction**
- **Ground vehicle identification from array microphones**

NEXT CHALLENGE: Biology Inspired Sensor Network processing

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Acoustic Vehicle Classification Objectives and Challenges

- Develop systematic methodologies and algorithms; not *ad hoc*
- Robust Target ID (wrt environment, terrain, speed)
- Algorithms for combined DOA (localization) and target ID
  - Localization assisted ID
  - ID assisted localization
- Multi-target detection, ID and DOA; separation of closely spaced targets
- Robust feature extraction from auditory models; dynamic DOA and ID
- Algorithm evaluation in the field and comparison against conventional algorithms for detection, DOA and ID

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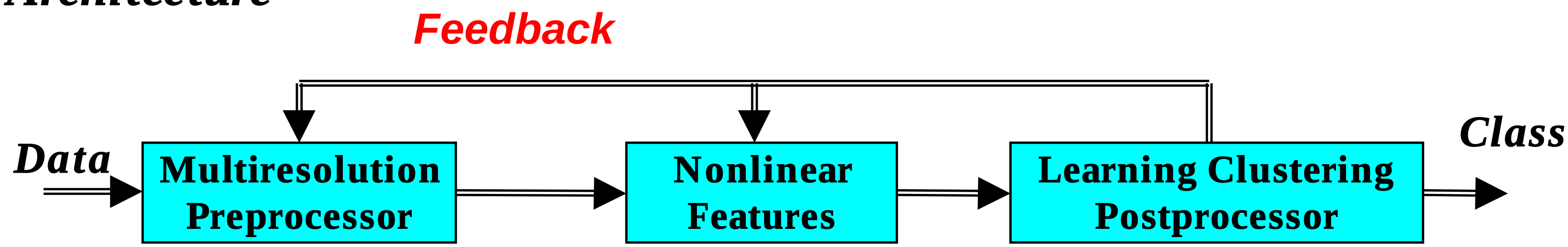
Multiresolution Adaptive Acoustic Classification

- ***Architecture***



- **Architecture and formulation address two most important issues:**
  - **Progressive classification; Which features to use and when**
  - **Efficient design of databases for reference signals and fast search**
- **Trade-off between efficiency in features (compression) and accuracy in classification leads to**
- **Mathematical formulation of the problem:**
  - **Combined compression and classification for general signals**
  - **Content-based feature extraction and use for classification**

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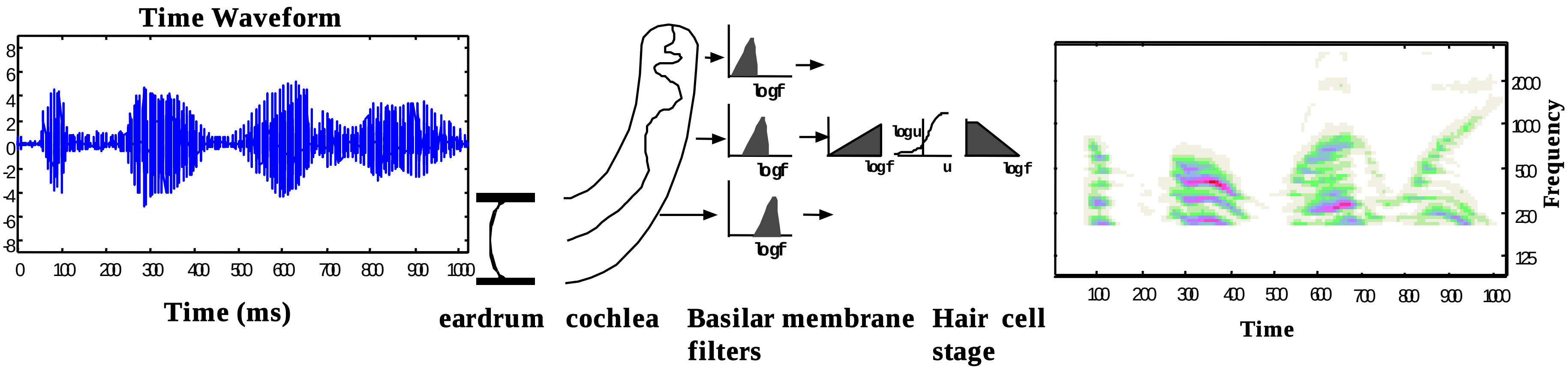
Multiresolution Preprocessor: Auditory Filtering

Two auditory filters, motivated and designed according to acoustic physiology and acoustic cortex models, were used to compute the timbre spectrogram of one particular subframe in each frame



- The first filter mimics the action of the inner ear
- Computes the spectrogram of the sound sample, and performs various nonlinear operations, which models the nonlinear fluid-cilia couplings and ionic channels of conduction

(Wavelet Transform)

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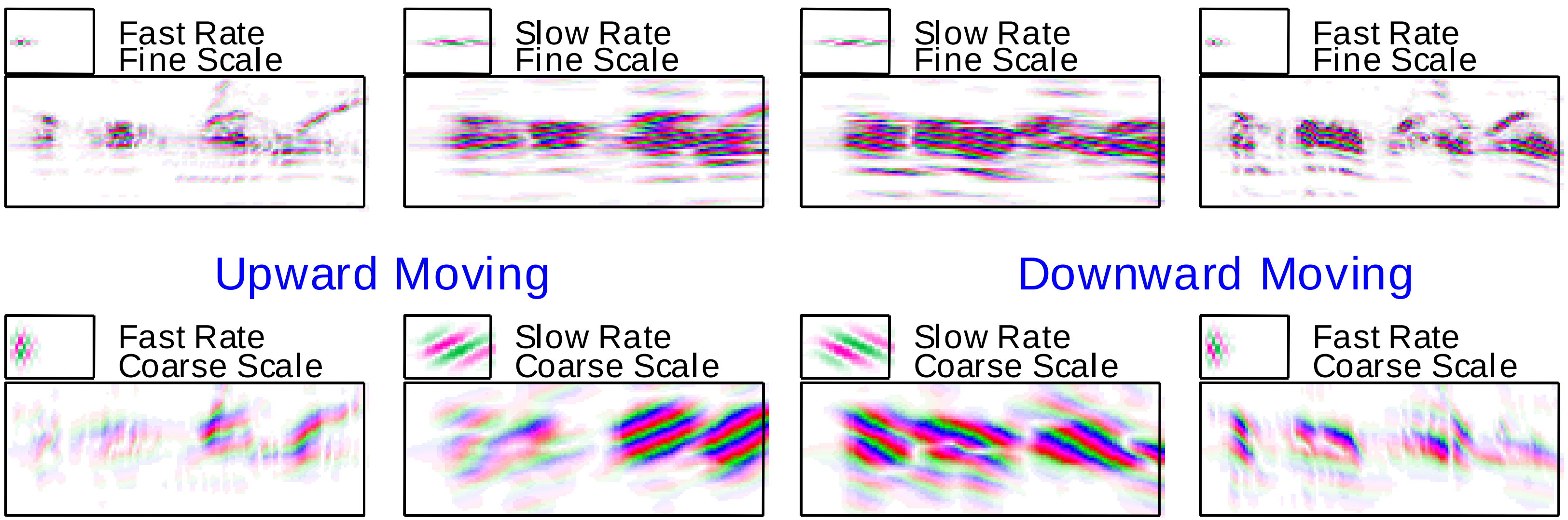
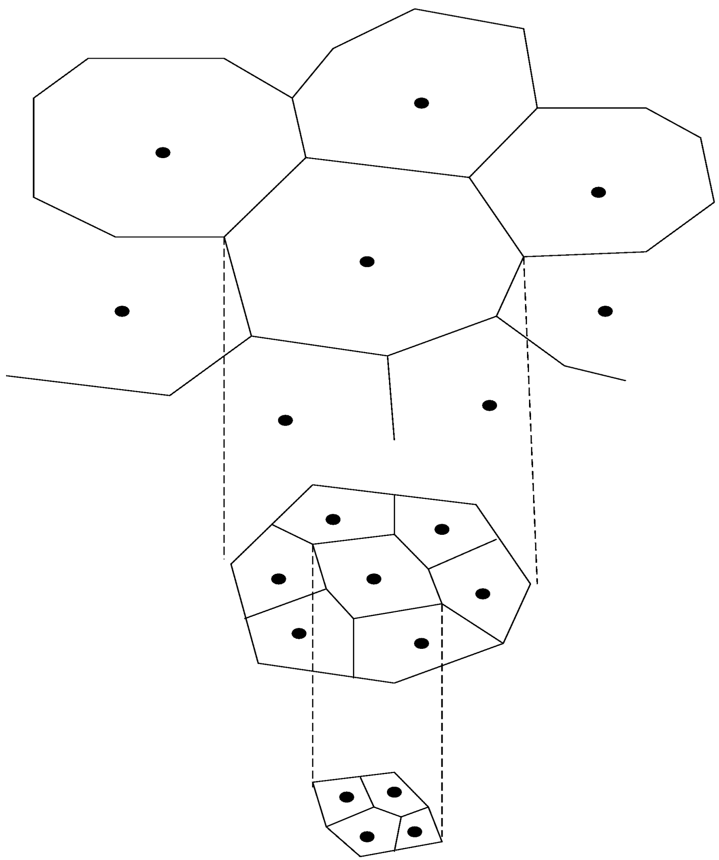
Multiresolution Preprocessor: Auditory Filtering

Multiresolution cortical filter outputs



- **The second filter models the multiscale processing of the signal that happens in the auditory cortex**
- **A Ripple Analysis Model, using a ripple filter bank, acts on the output of the inner ear to give multiscale spectra of the sound timbre (Wavelet Transform)**

Postprocessor: Multi Resolution (Wavelet) Tree Structured Vector Quantization (WTSVQ)



- First perform a multiresolution wavelet representation of the signals
- Consider each signal f at different resolutions

  $S^0 f, \; S^1 f, \ldots, \; S^{J^*} f$
- Proceed by partitioning the signal space at various resolutions in progressively finer cells
- *Greedy algorithm* works by splitting the cell with maximum distortion using finer resolution data

Layer in tree $l = J^* - m$, m the scale (top layer 0: coarsest)

Cell labels: (layer, index) or (scale, index)

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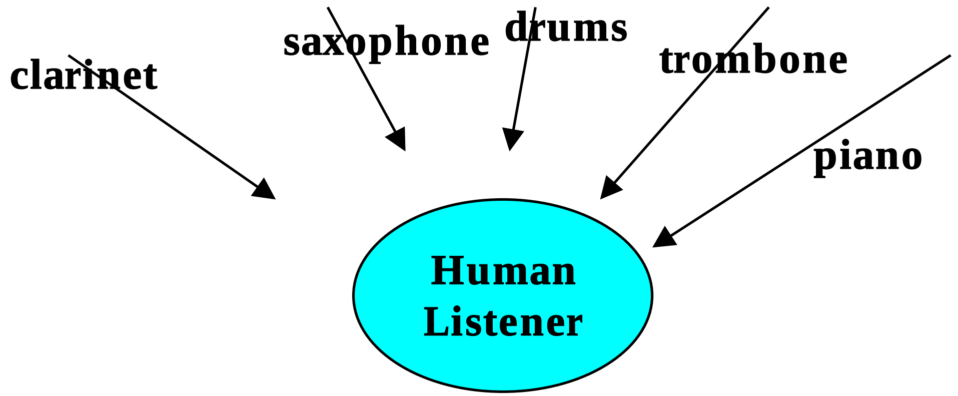
Approach

Can we mimic and understand the ability of humans to do partial recognition of musical instruments and DOA in a combined and mutually enhancing fashion?



- Combine the Stereausis model and its derivatives , with the Auditory filtering multiscale VQ algorithms
- Using the cochlea, cortical, or combined spectra, perform DOA on a “per frequency band basis”
- Combine portions of spectra according to DOA
- Use the multiscale classifier to ID portions of spectra tagged by angle, as compared to stored vehicle spectra
- Repeat the cycle as the scenario evolves

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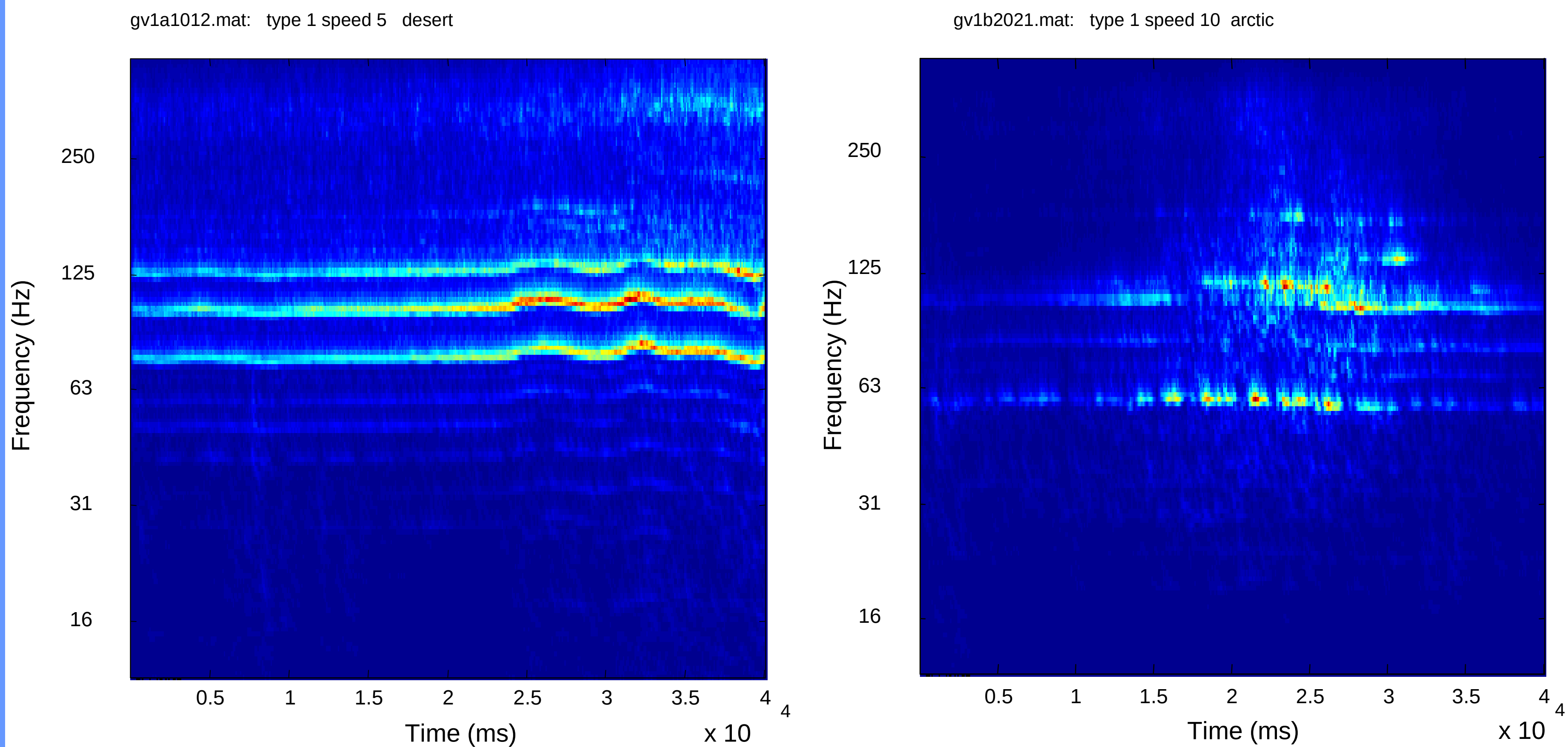
Auditory Processing of Vehicle Acoustic Signals: Cochlea



Auditory processing for vehicle signals (cochlear filter banks)
Left: vehicle type 1, speed 5km/hr. Right: vehicle type 1, speed 10km/hr

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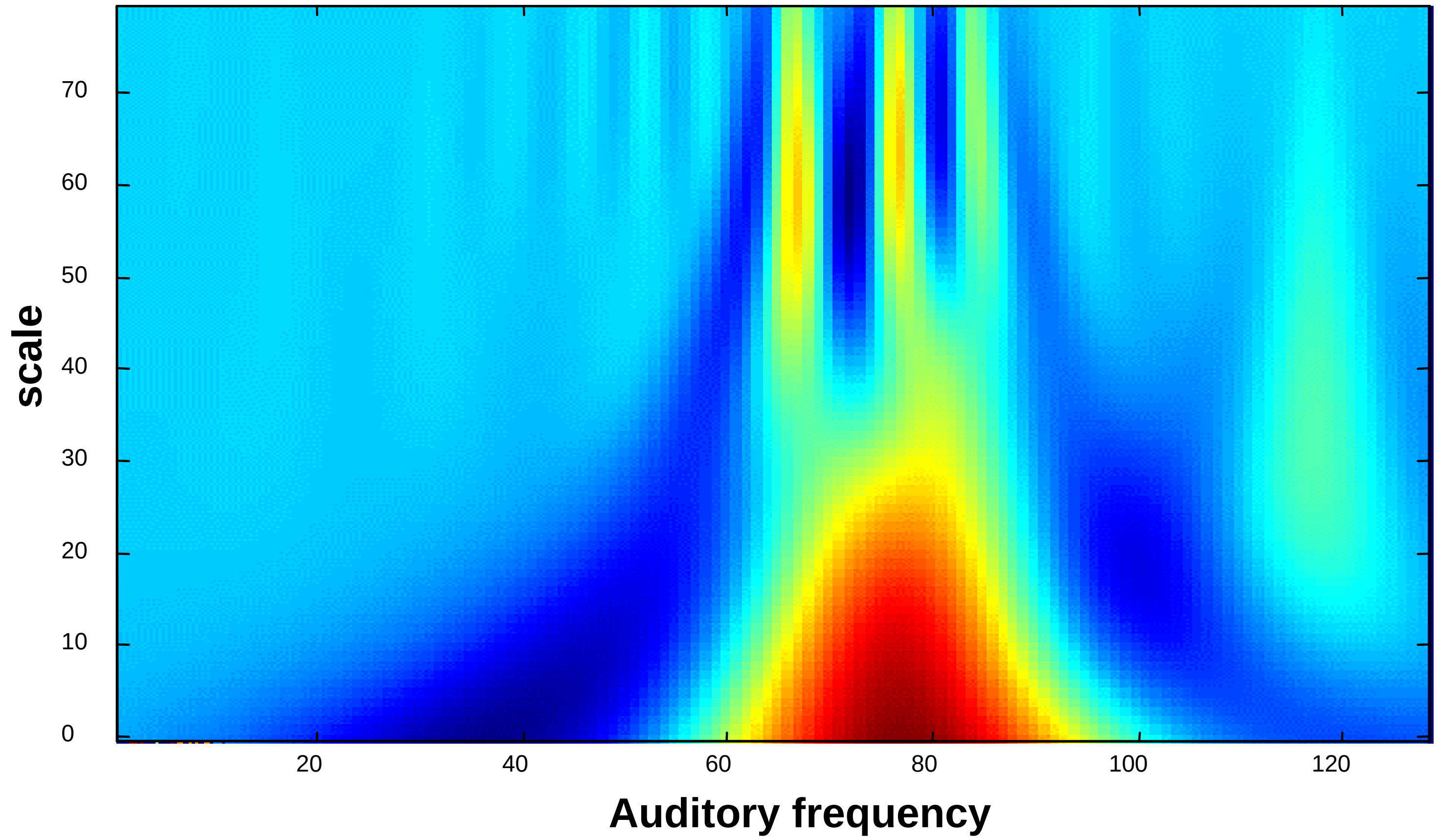
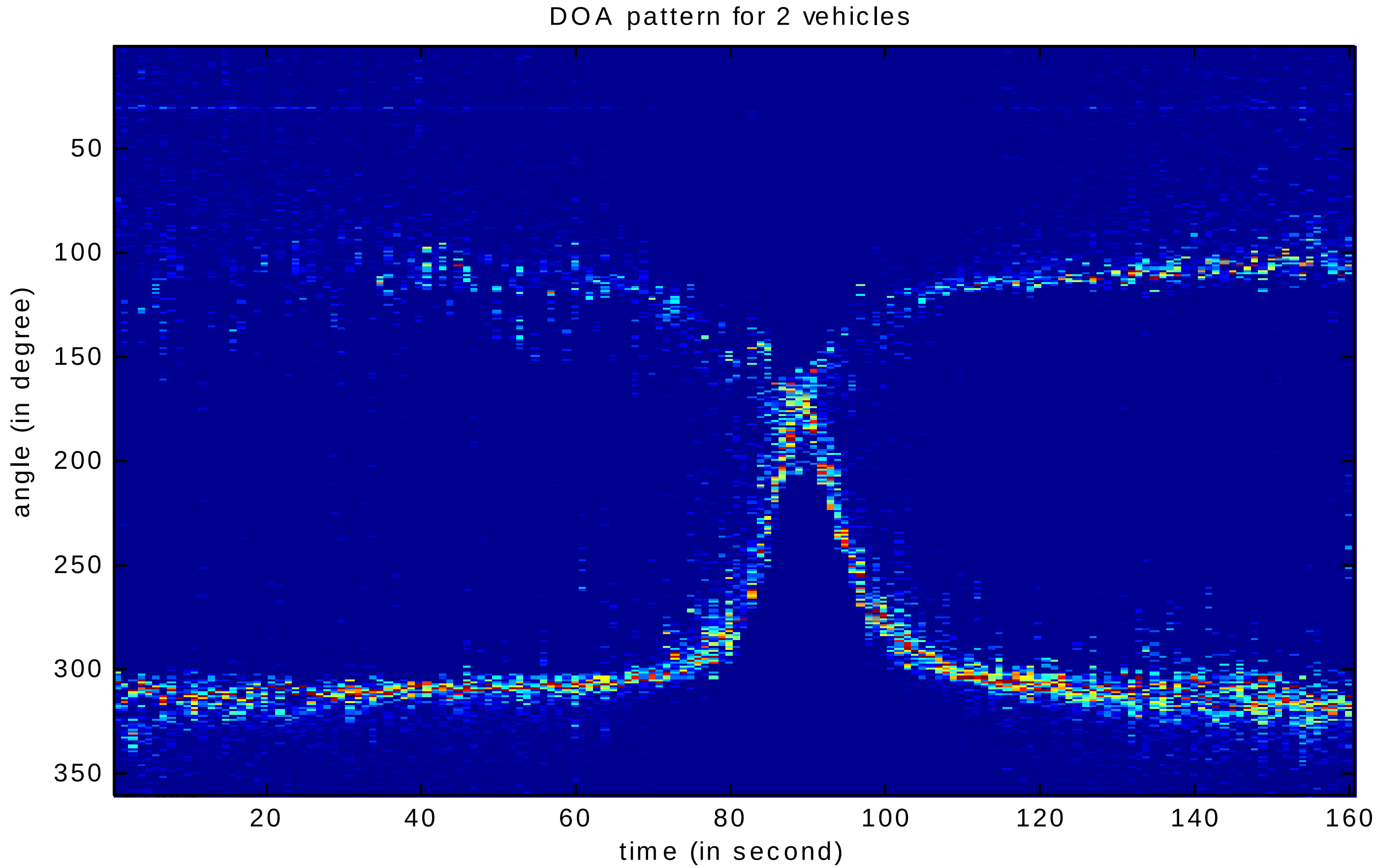
Auditory Processing of Vehicle Acoustic Signals: Cortex



Example of multi-resolution representation from cortical module

Stereausis Output for Two Vehicles



Relatively easy case: Large angular separation between two vehicles

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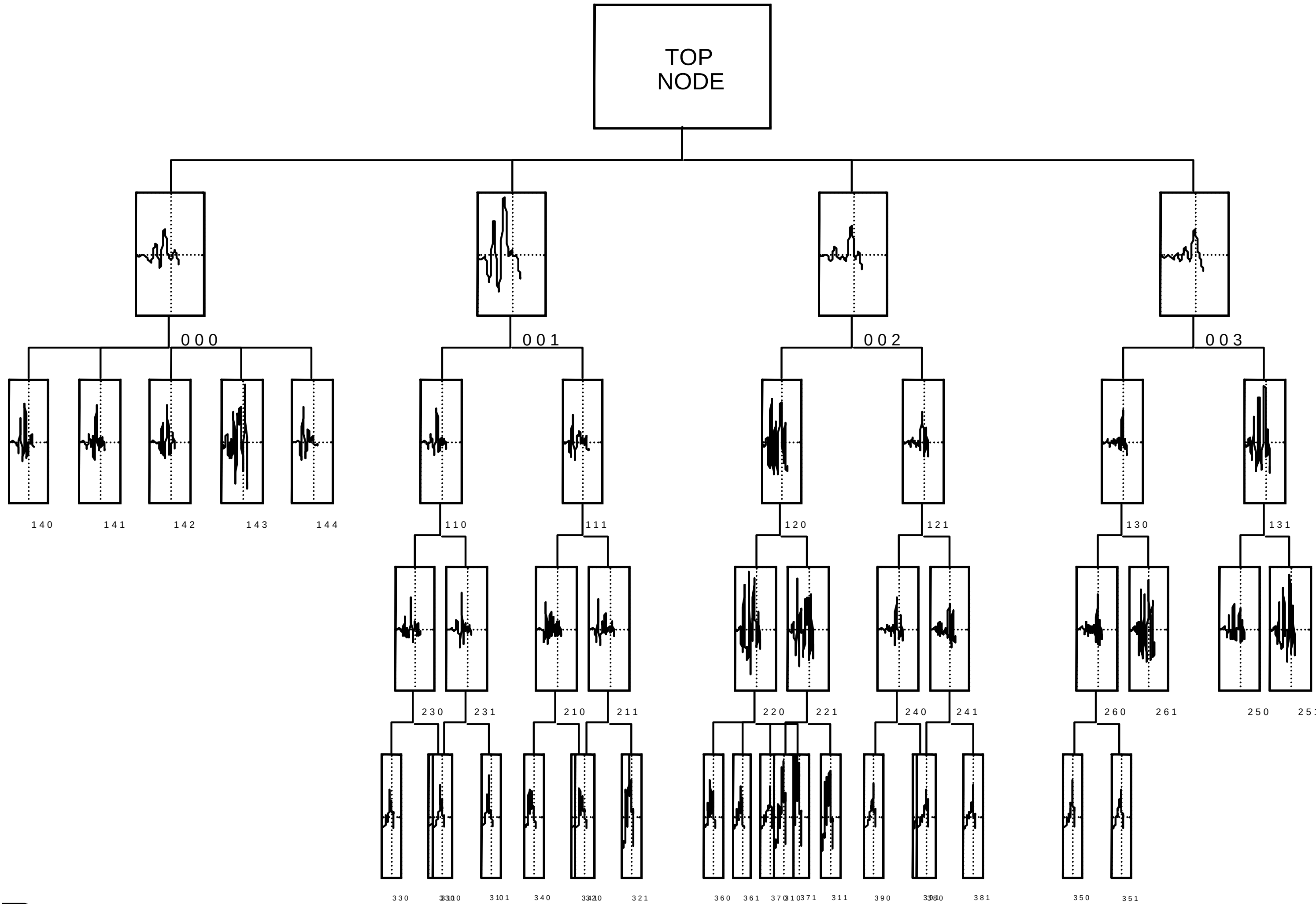
Leaf Node Entropies for PTSVQ Tree of Vehicle Type 8

cell entropy

1 4 0	1.3570
1 4 1	0.9503
1 4 2	1.1779
1 4 3	1.0735
1 4 4	1.3022
2 5 0	0.6365
2 6 1	0
3 1 0	0.5765
3 1 1	0.2993
3 2 0	0.7516
3 2 1	0.4765
3 3 0	0.7633
3 3 1	0.5670
3 4 0	0.4540
3 4 1	0.4384
3 5 0	0.2728
3 5 1	0.4975
3 6 0	0.5313
3 6 1	0.3061
3 7 0	0.6054
3 7 1	0.6383
3 8 0	0.4824
3 8 1	0.5377
3 9 0	0.5044
3 9 1	1.2556
3 10 0	1.0144
3 10 1	1.1967



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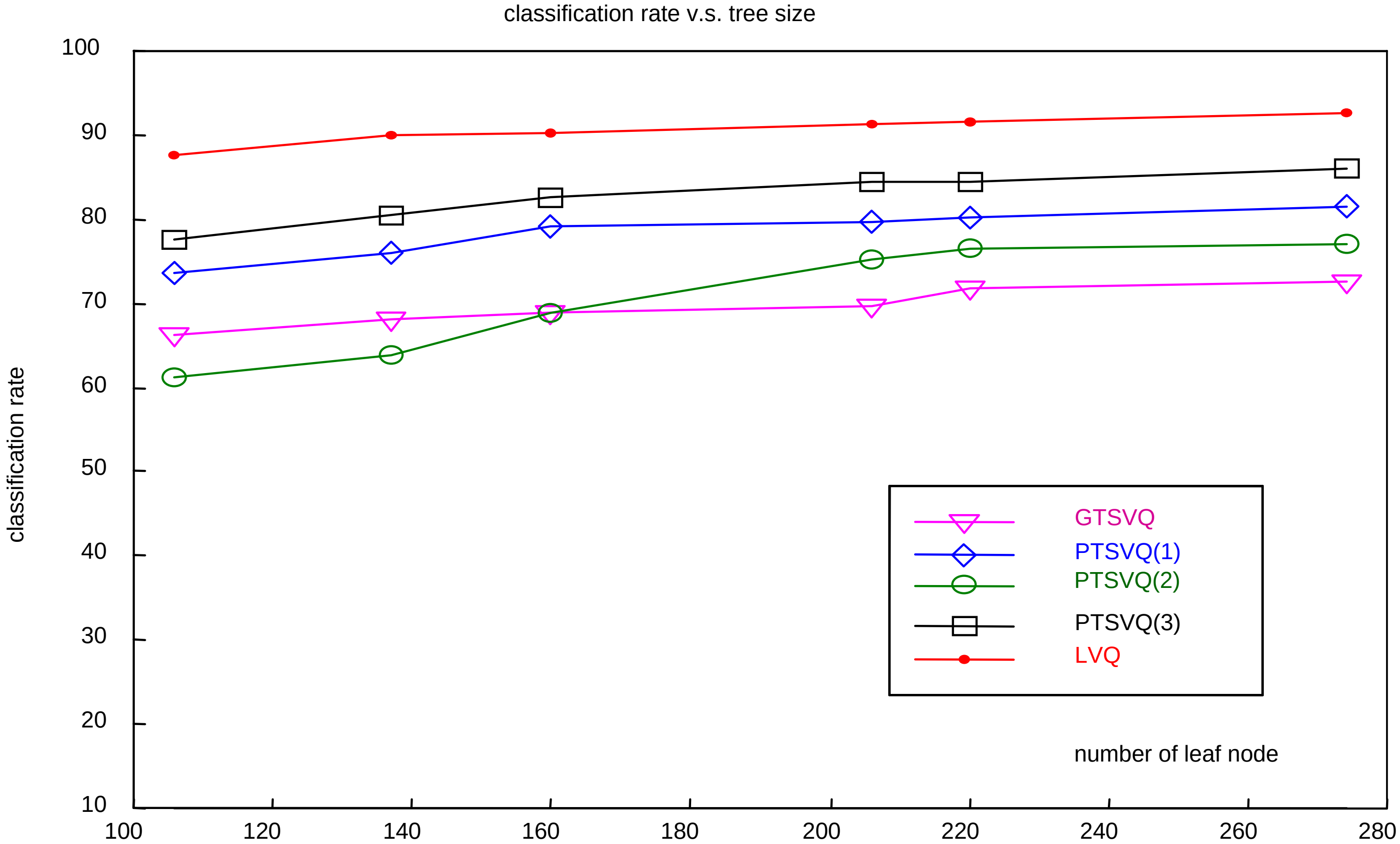
Options in Applying WTSVQ to Acoustic Vehicle Classification

- **GTSVQ: A global tree-structured multi-resolution clustering mechanism that mimics the aggressive and topological hearing capabilities of biological systems. Here a global tree is built on training data from all vehicles. New vehicle insertion problem.**
- **LVQ: A supervised learning neural network, LVQ achieves optimal classification in the Bayes sense. It has the disadvantages of a long search time and sensitivity to initial conditions.**
- **Parallel TSVQ (PTSVQ): build one (or more) trees for each vehicle. It achieves a trade-off between GTSVQ and LVQ on classification performance and search time. Easy new vehicle insertion.**
- **The following node allocation schemes are examined for PTSVQ:**
  - **PTSVQ(1): Allocation based on sample a priori probability**
  - **PTSVQ(2): Allocation based on equal distortion**
  - **PTSVQ(3): Allocation according to vehicle speed**

Performance Comparisons among Options



Classification Performance: 70% samples for training, 30% for testing (same microphone)

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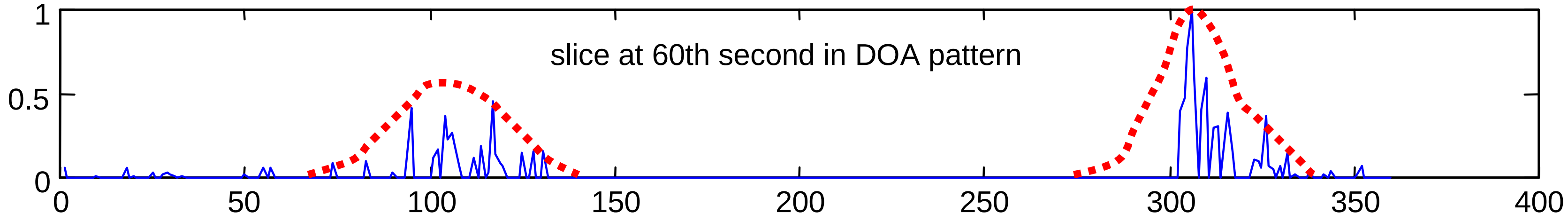
Tagging Portions of Spectra Based on "per Band" DOA Estimates

- Angular position of ach peak corresponds to DOA estimate from each cochlea band
- Can use up to 128 bands
- Amplitude indicates signal energy in the band



- Low pass filtering is performed on groups of band amplitudes and the resulting peak is used as the DOA estimate for the vehicle
- Cluster according to angular position of peaks: spectral portions tagged by angle